Optimization of SVM Classifier by k-NN for the Smart Diagnosis of the Short-Circuit and Impedance Faults in a PV Generator

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Abstract – *This paper deals with a new algorithm allowing short-circuit and impedance faults smart diagnosis of PV generators. It is based on the use of the SVM technique for the classification of observations not located in its margin, otherwise the proposed algorithm is used a k-NN method.*

A PV generator database containing observations distributed over classes is used for testing the new algorithm performance, which shows therefore its contribution and its effectiveness in the diagnosis area.

Keywords: *Photovoltaic Generator, SVM, k-NN, Short-circuit, Impedance, Smart Diagnosis.*

Nomenclature

PV	Photovoltaic.
SVM	Support Vector Machines.
k-NN	k-Nearest Neighbor.
CO	Class of Observation.
Y	SVM output vector.
f	Linear function.
Φ	Nonlinear mapping function.
K	Kernel matrix.
w	Weight vector.
X	Observations matrix.
x^*	New observation.
C	Class addition.
α	Lagrange multipliers.
c_i	Class number i.
D	Y diagonal.
T	Transpose.
N	Number parameters of observation.
M	Classes number.
m	Observations number in X.
x_{ji}	Parameter j of observation x_i.
x_j^*	Parameter j of new observation x^*.
I'	Identity matrix.
J	Tuning parameter for error accepted.
I	Current.
V	Voltage.
P	Power.
PH	Photocurrent.
I/V_{Cell}	Current / Voltage of PV cell.
I/V_{Group}	Current / Voltage of PV group.
I/V_{Module}	Current / Voltage of PV module.
I/V_{String}	Current / Voltage of PV string.
I_{Bypass_Diode}	Bypass diode current.
R_s	series resistance.
t	Temperature.

I. Introduction

The Earth receives every year a huge amount of energy from the sunlight. Indeed, it receives on average 170 W/m² on its surface. However, photovoltaic solar panels are not able to recover all of this energy. Thus, the amount of the usable energy created by the PV solar panels, divided by its radiation energy received is the performance [1]-[2]. Among the major factors that influence the photovoltaic generators performance, the presence of electrical defects such as: short circuit and impedance. It is possible to ensure a good control [3]-[5] and diagnostic [6]-[8] functions of the PV generators, to reduce its maintenance costs and especially increase its productivity.

In this context, the paper objective is the development of an algorithm of a short-circuit and impedance faults smart diagnosis, in a photovoltaic generator. Indeed, the paper contributions are twofold: *1)* Development of short-circuit and impedance detection and localization algorithm, it bases on the analysis of the parameters characterizations, of the faulty components: cells, bypass, and blocking diodes. *2)* Development of a smart classifier, to detect the PV generator faults, it used the observations collected from the control system. It is based firstly on the support vector machines (SVM) technique, for the classification of observations not located in its margin [14]-[17], and secondly on the k-NN method in the opposite case [18]-[20].

II. Classical Diagnosis Algorithm

The studied generator as it presented in the following Fig. 1 contains five strings connected in parallel. Each string contains five modules in series, and ended by blocking diode. Each module contains two groups in series. And finally, each group contains eighteen cells in series, regrouped by one bypass diode in parallel. The proposed diagnosis algorithm is designed for the classical detection and localization, of short-circuit and impedance faults in a PV generator. It contains four main steps:

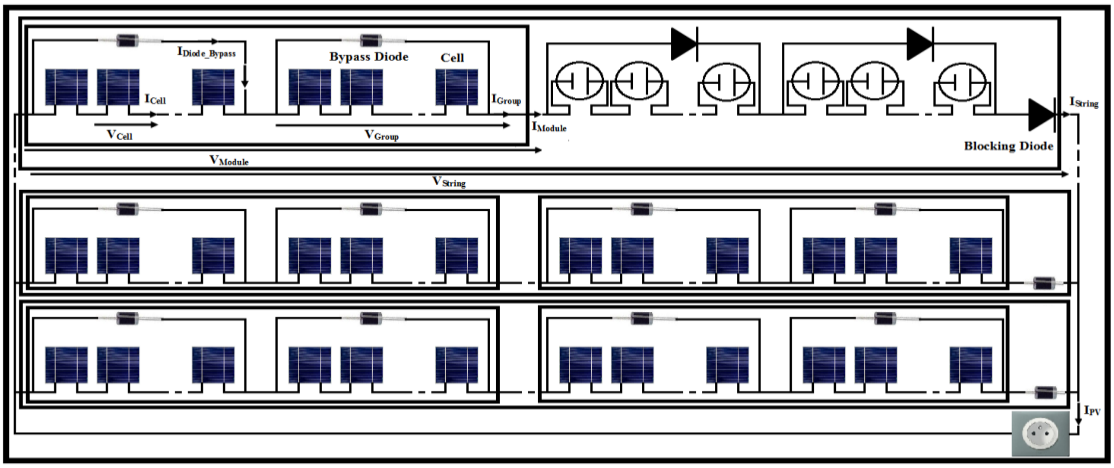

Fig.1 . Photovoltaic generator described

A) Step1: If a PV generator characteristic is

$$\begin{cases} V_{PV} = 0 \\ I_{PV} = I_{PV\_Short-Circuit} \end{cases} \quad (1)$$

means that the generator is short-circuited. But if its characteristic is

$$\begin{cases} -V_{PV\_Opposite} \le V_{PV} \le V_{PV\_Healthy} \\ -I_{PV\_Opposite} \le I_{PV} < I_{PV\_Short-Circuit} \end{cases} \quad (2)$$

indicates the presence of generator components impedance, which can cancel its power, or change its functioning to a receptor.

B) Step2: the PV string is short-circuited if its characteristic is

$$\begin{cases} I_{String} = I_{String\_Short-Circuit} \\ V_{String} = 0 \end{cases} \quad (3)$$

But, if its characteristic is

$$\begin{cases} V_{String} = V_{String\_Opposite} \\ I_{String\_Cells} = 0 \\ I_{String} = I_{String\_Opposite} < 0 \\ I_{String\_PH} = 0 \end{cases} \quad (4)$$

indicates the presence of blocking diode short circuited. Also, if its characteristic is

$$\begin{cases} I_{String} \ge I_{String\_Healthy} \\ I_{PH\_String} \ne 0 \\ I_{String\_Opposite} = 0 \\ V_{String} < V_{String\_Healthy} \\ \sum V_{String\_Modules} = V_{String} \end{cases} \quad (5)$$

means the presence of at least one module impedance. Or, if its characteristic is

$$\begin{cases} I_{String\_Cells} = 0 \\ I_{String\_PH} = 0 \\ I_{String} = I_{String\_Opposite} < 0 \\ V_{String} = V_{String\_Opposite} \end{cases} \quad (6)$$

indicates the presence of default blocking diode impedance.

C) Step3: A PV module is short-circuited if its characteristic is

$$\begin{cases} I_{Module} = I_{Module\_Short-Circuit} \\ V_{Module} = 0 \end{cases} \quad (7)$$

This situation means that all its groups are short-circuited. But, if its characteristic is

$$\begin{cases} I_{Module\_Groups} \ge I_{Module\_Healthy} \\ I_{PH\_Module} \ne 0 \\ I_{Module\_Opposite} = 0 \\ V_{Module} \le V_{Module\_Healthy} \\ \sum V_{Module\_Groups} = V_{Module} \end{cases} \quad (8)$$

means the presence of least one group impedance.

D) Step4: if a PV group characteristic is

$$\begin{cases} I_{Group} = I_{Group\_Short-Circuit} \\ V_{Group} = 0 \end{cases} \tag{9}$$

means that the group is short-circuited. Also, if its characteristic is

$$\begin{cases} I_{Group} = I_{Group\_Cells\_Short-Circuit} + I_{Bypass\_Diode} \\ V_{Group} = 0 \end{cases} \tag{10}$$

indicates the presence of all the group cells are short-circuited. In addition, if its characteristic is

$$\begin{cases} I_{Group} = I_{Group\_Cells\_Healthy} + I_{Bypass\_Diode} \\ V_{Group} = 0 \end{cases} \tag{11}$$

means that the group is connected by a bypass diode short-circuited. But, if its characteristic is

$$\begin{cases} I_{Group\_Cells} = 0 \\ I_{Group} = I_{String} \\ I_{PH\_Group} \neq 0 \\ I_{Group\_Opposite} = 0 \\ V_{Group} = 0 \end{cases} \tag{12}$$

indicates the default all the group cells are impedances. Or, if its characteristic is

$$\begin{cases} I_{Group} > I_{Group\_Healthy} \\ I_{PH\_Group} \neq 0 \\ I_{Group\_Opposite} = 0 \\ V_{Group} = V_{Group\_Healthy} \end{cases} \tag{13}$$

means the presence of bypass diode impedance.

III. Intelligent Diagnosis Algorithm

III.1. SVM algorithm

This technique is a method of two-class classification, which attempts to separate the positive examples from which are negative, in the same space.

The method seeks the hyper-plane that separates the positive examples from which are negative, by ensuring that the margin between the nearest of the positive and negative examples is maximum. This ensures a generalization of the principle, as new examples may not be too similar to those used to find the hyper-plane, but be located on one side or the other of the border.

The advantage of this method is the selection of support vectors, which represent the discriminate vectors by which the hyper-plane is determined. The examples used in the search of the hyper-plane are no longer needed, and only those supports vectors are used to assign a new case, which can be seen as an advantage for this method. This technique consist mainly two steps:

1) Step1: construct the SVM Classifier

The objective is to construct a function *f*, which for each input value *x* in a set $\mathbb{R}^d$ will match an output value y$\in$ {-1,1}. The following model describes the learning function *f* in the linear case and also in the non-linearly, but after changing the data space to another with a larger dimension, by the nonlinear mapping function *Φ*.

$$f(x) = \begin{bmatrix} \text{If the problem is linear separable} \\ sign\left(\left\langle w_{c,\mathbb{C}(c)}.x \right\rangle + b_{c,\mathbb{C}(c)}\right) \\ \text{Else} \\ sign\left(\left\langle w_{c,\mathbb{C}(c)}.\phi(x) \right\rangle + b_{c,\mathbb{C}(c)}\right) \\ \text{End} \end{bmatrix} \tag{14}$$

2) Step2: determining the Hyper-Plane

In the new space data, there are many hyper-planes separating, the best is which maximizes the margin between its location and the support vectors. The following model describes the hyper-plane optimal resulting by the linear programming to found the parameters of the *f* function.

$$f(x) = \begin{bmatrix} \text{If the problem is linear separable} \\ sign\left(\alpha^T_{c,\mathbb{C}(c)} Xx + \frac{1}{y_i}\left(1 - \alpha_{c,\mathbb{C}(c)}\left(DKD + \frac{1}{J} I'\right)\right)\right) \\ \text{Else} \\ sign\left(K\left(x, X^T\right) D\alpha_{c,\mathbb{C}(c)} + \frac{1}{y_i}\left(1 - \alpha_{c,\mathbb{C}(c)}\begin{pmatrix} DKD \\ + \frac{1}{J} I' \end{pmatrix}\right)\right) \\ \text{End} \end{bmatrix} \tag{15}$$

SVM and like all classification techniques, it has some drawbacks mainly: 1) the binary classification which need to solved the problem by a set of equations, each one presents a classifier between a class and its complement, except classes already processed. 2) The classification of new examples which are located in the SVM margin, and especially if this margin is not well maximized. In this paper we propose for the latter problem as a solution, using the classical method k-NN.

III.2. k-NN method

This is a very simple and straightforward approach. It does not require learning, but simply storing training data. Its principle is as follows:

1) Step1: *k-NN* compares the new example *x** of unknown class, to the all oldest examples in its databases *X*.

$$X^{t+1}=\begin{bmatrix} Dis\left[x_1-x^*\right] \\ Dis\left[x_2-x^*\right] \\ \vdots \\ Dis\left[x_m-x^*\right] \end{bmatrix} \tag{16}$$

With
m: examples number of X^t.
Dis: distance.

2) Step2: *k-NN* chooses for this new example the majority class among its *k* nearest neighbors (so it can be cumbersome for large databases) as defined by a selected distance.

$$x^* \in Class\ of\ \ Observations\ of\ \ Dis\ minimum \tag{17}$$

C. The Proposed Smart Algorithm

Our contribution in this section is to develop a mathematical model bases on the tools presented above. It is able to make a smart classification of a PV generator defects, aims to increase the classification rate, and at the same time to minimize the classification error rate. In this proposed model, we used for the activation function of SVM the Gaussian type, and for the k-NN method using the Euclidean distance between the gravity centers of database observations.

$$f\left(x^*\right)=(1-\xi)\begin{bmatrix} \text{If the problem is linear separable} \\ \begin{bmatrix} sign\left(\alpha^T_{c_1,\complement(c_1)}Xx^*+\dfrac{1}{y_i}\left(1-\alpha_{c_1,\complement(c_1)}\left(DKD+\dfrac{1}{J}I'\right)\right)\right) \\ \vdots \\ sign\left(\alpha^T_{c_{M-1},c_M}Xx^*+\dfrac{1}{y_i}\left(1-\alpha_{c_{M-1},c_M}\left(DKD+\dfrac{1}{J}I'\right)\right)\right) \end{bmatrix} \\ \text{Else} \\ \begin{bmatrix} sign\left(K\left(x^*,X^T\right)D\alpha_{c_1,\complement(c_1)}+\dfrac{1}{y_i}\left(1-\alpha_{c_1,\complement(c_1)}\left(DKD+\dfrac{1}{J}I'\right)\right)\right) \\ \vdots \\ sign\left(K\left(x^*,X^T\right)D\alpha_{c_{M-1},c_M}+\dfrac{1}{y_i}\left(1-\alpha_{c_{M-1},c_M}\left(DKD+\dfrac{1}{J}I'\right)\right)\right) \end{bmatrix} \\ \text{End} \end{bmatrix}+\xi * CO\left(index\left[\min\begin{bmatrix} \dfrac{1}{N}\sum_{j=1}^{N}\left|x_{j1}-x_j^*\right| \\ \dfrac{1}{N}\sum_{j=1}^{N}\left|x_{j2}-x_j^*\right| \\ \vdots \\ \dfrac{1}{N}\sum_{j=1}^{N}\left|x_{jm}-x_j^*\right| \end{bmatrix}\right]\right) \tag{18}$$

Where ξ = 1 if x is in the margin of the SVM classifier, else ξ = 0.

IV. Simulations Results

IV.1. Faulted PV Generator Characterization

The main simulation results of the diagnostic algorithm are shown by Figs. 2 to 4.

1) Fig. 2 presents the evolution of the power supplied by a generator contains cells short-circuit and impedance. It therefore shows that the power of a PV generator is reduced in proportion to the increase in the numbers of its defective cells.

2) Fig. 3 presents the influence of short-circuited and impedance faults at the bypass diodes, on the functioning of a photovoltaic generator. It shows that the bypass diode short-circuit defect *a)* affects the group voltage, but the current remains independent, unless all its string groups are failed. By const, it shows that the impedance defect *b)* has no influence on the characterization of a faulty string, which contains at least one good group, *c)* else the power of the generator increases, proportionally to the increase in the number of strings which all its groups are defective, because its currents are increases, until reaches its short-circuit value.

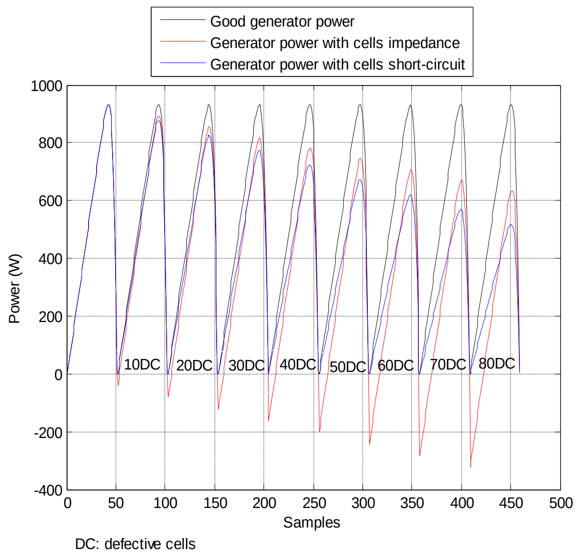

Fig2. Short-circuit and impedance cells influence on the PV generator operation.

3) Fig. 4 presents the influence of the blocking diode short-circuited and impedance faults, on the functioning of a photovoltaic generator. It shows that these defects can make a remarkable deterioration in the power supplied by a generator, because the blocking diode short circuit default, with another defect which can reduce its

string voltage, and also for the blocking diode impedance default which may reduce the voltage of its string, so these two situations can create the reverse current in its strings, and therefore change its characterizations to a receivers in the absence of the photocurrent, or becomes as open circuit in the opposite case.

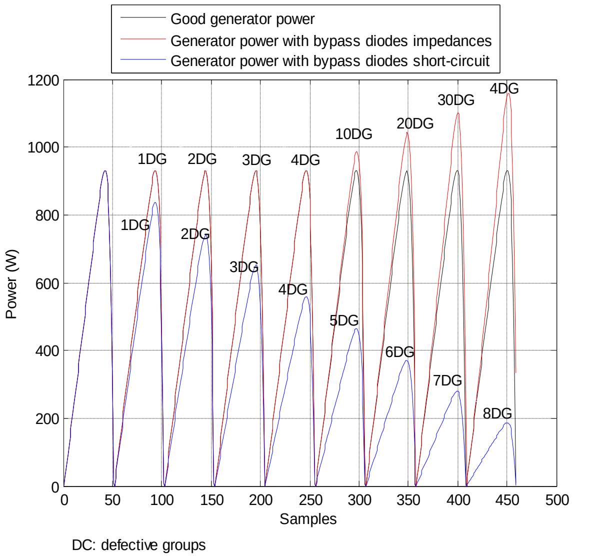

Fig3. Short-circuit and impedance bypass diodes influence on the PV generator operation.

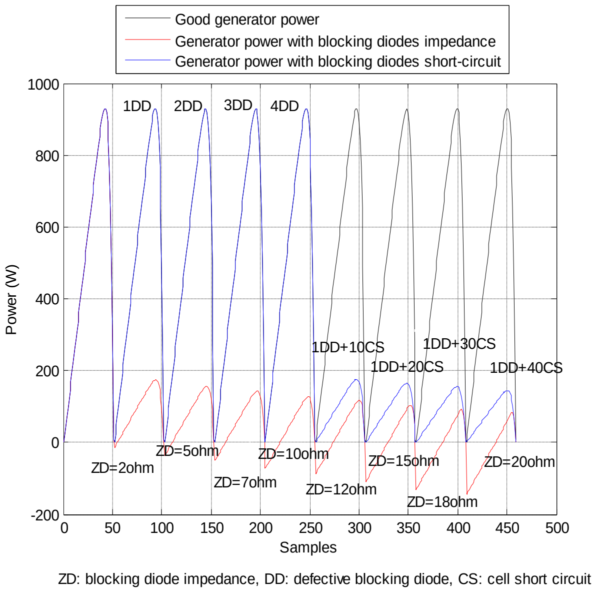

Fig4. Short-circuit and impedance blocking diodes influence on the PV generator operation.

IV.2. Smart Algorithm Tests

The proposed smart fault detection and diagnosis algorithm is tested using a PV generator database containing observations (Tab. 1) distributed over classes (Tab. 2) [24-25]. For that purposes, three indicators are used: the rate of good classified observations (Figs. 5-6), the computation time to classify any new observation (Fig. 7), and finally the classification error rate (Figs. 8-9).

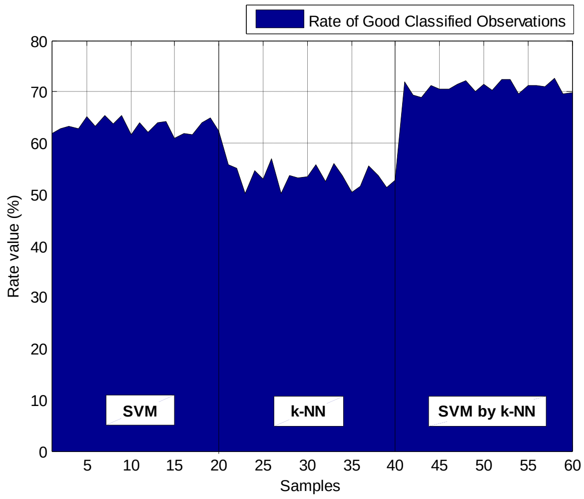

Fig. 5. Observation classification rate *vs* tools.

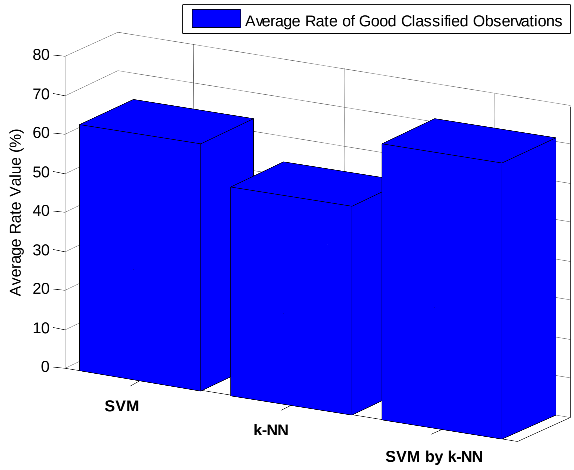

Fig. 6. Observation classification average rate *vs* tools.

TABLE.1. OBSERVATION CLASS

Class	normal operation	defective cells	defective bypass diodes	defective blocking diodes
Number of observations '*X*'	1632	1632	1632	1632

TABLE.2. OBSERVATION PARAMETERS

Parameters	I	V	P	R_s	T	I_{ph}

Each observation is presented by its center of gravity '*x*'.

The achieved results (Figs. 5-6) show that the rate of good classified observations is

TABLE.3. RATE OF GOOD CLASSIFIED OBSERVATIONS

Classifier	SVM	k-NN	SVM_k-NN
Rate (%)	60 to 69.9	50 to 53.5	68 to 75.8%

The achieved results (Fig. 7) show that the computation time is

TABLE.4. NEW OBSERVATION CLASSIFICATION ELAPSED TIME

Classifier	SVM	k-NN	SVM_k-NN
Computation Time (second)	5.5 to 7	2 to 3	5 to 10

The achieved results (Figs. 8-9) show that classification error rate is

Tab.5. Classification Error Rate

Classifier	SVM	k-NN	SVM_k-NN
Rate (%)	0.8 to 0.9	1.5 to 2	0.36 to 0.55

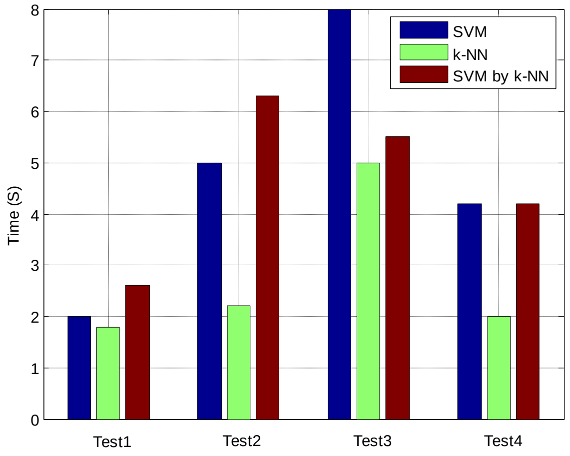

Fig. 7. New observation classification elapsed time *vs* tools.

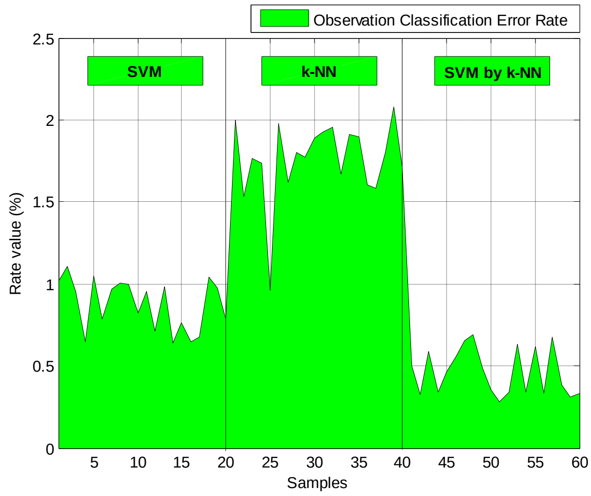

Fig. 8. Observation classification error rate *vs* tools.

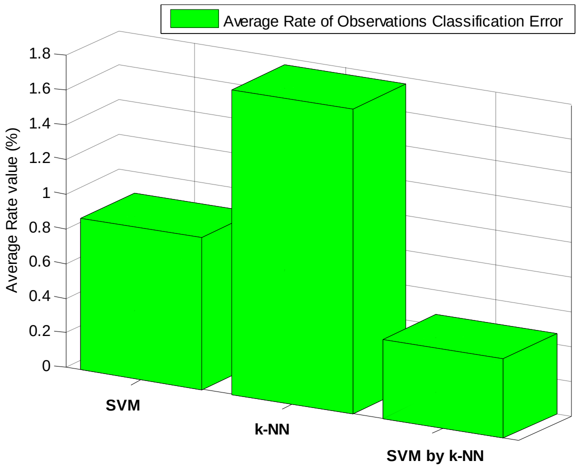

Fig. 9. Observation classification error average rate *vs* tools.

The analysis of the above achieved results shows that the proposed new classifier has a high classification rate, with a low error rate, but it is a little bit time consuming, due the mathematical computations.

IV. Conclusion

This paper dealt with a new smart algorithm allowing short-circuit and impedance detection and diagnosis in PV generators. It is based on the optimization of SVM classifier, firstly by solving a set of equations as a solution to the problem of multi-class. And secondly by k-NN as a solution to the classification of observations, which located on the SVM classifier itself and its margin.

The new algorithm proposed in this paper shows its specific features: a high classification rate with a low error rate. But, it is a little bit time consuming due the mathematical computations, which necessities to more improvement in the future work as perspective.

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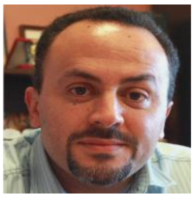

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